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***Case Study***

# Comparing SARIMA and Adjusted SARIMA models using output based criterion: A case study of Warri monthly rainfall

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## Abstract

*The paper models Warri monthly rainfall (WMRF) pattern by comparing SARIMA and Adjusted SARIMA (ASARIMA) models using output based criterion. The rainfall data set used covered the period of 1981M1-2016M12. The ADF unit root tests showed that rainfall data is integrated order zero (I(0)). But ACF and PACF exhibit need for seasonal differencing as there are seasonal effects with periodic peaks at lag 12 and 24. The SSDFC was used to compare thirty one models: 17 possible SARIMA (p, d, q) x $(P, D, Q)_{12}$ models with 14 possible ASARIMA $(P, D, Q)_{12}$ models. Result indicates that ASARIMA $(1,1,3)_{12}$ is most appropriate. The diagnostic tests indicate adequacy of the fitted model. Hence, the fitted model is recommended for forecasting WMRF pattern and creating short-term warning against flood in the state.*

**Keywords:** ASARIMA model, WMRF, SARIMA, SSDFC

## Introduction

Rainfall is one of the major components of water cycle and is responsible for depositing some good volume of fresh water on the earth. Empirically, different models have been used by various researchers for modelling rainfall data. Warri as one of the major oil city in Delta State, Nigeria, with a population of over 300,000 people according to the national population figures for 2006. The people of Warri are mainly the Urhobos, Isokos, Itsekiris, and Ijaws, but other ethnic groups also live within the city. Warri city is one of the oil hub in South-Southern Nigeria and served as the colonial capital of the then Warri Province. It shares boundaries with Sapele, Okpe, Ughelli /Agbarho, Udu and Uvwie. Although, most of these places, notably Uvwie, Okpe, and Udu have been integrated into the larger metropolitan areas of Warri. The airport that serves the city is located at Osubi. A place called Effurun serves as the gateway to and the economic nerve of the Warri city. Its geographical coordinates are $5^0$31’0” North, $5^0$45’0” East based on weather reports collected during 2006–2015. The climate and weather averages all through the year in Warri reveals; High Temp: 93°F, Low Temp: 71°F and Mean Temp: 8°F. Rainfall as a vital natural phenomenon is useful for agricultural productions all over the world[1,2].

The pattern of extreme high or low rainfall in any environment is very important for agriculture as well water reservation. The mean annual rainfall symbolizes long-term quality of water available to a region or state for hydrological and agricultural purposes. Situations where there is no irrigation, it provides maximal water available for the regions to sustain agricultural potentials in regard to biomass production if other factors (such as light, temperature, topography, soils) are not limited. Annual precipitation however, is not only vital for agricultural purposes but also, one of the strongest determinants of tropical micro climate known to hydrologist. Despite advances made in weather forecasting, accurate rainfall forecasting has been the most challenging task in operational hydrology[3].

Water is a necessity and essential for the development and maintenance of the dynamics of every ramification of the society[4]. The problem of source of portable drinking water has become a challenge to many states in the Niger Delta region due to enormous oil spillage which caused environmental hazards and polluted our waters which served as sources of good drinking water supply to many homes. So, studying monthly rainfall pattern in Warri and generating forecasts values of the monthly rainfall can be useful in the formulation of agricultural policies and adequate environmental and water resource management in the state. Thus, it becomes essential to undertake this research.

Many researchers have given much attention on the trend pattern of rainfall and some have shown interest towards modelling and forecasting the amount of rainfall pattern in various parts of world including Nigeria. For instance, a sudden change in rainfall characteristics in Amman, Jordan during the Mid 1950s was examined and the study covered a period of 81 years (1922-2003). And the results revealed different trends for different seasons across the three stations observed, however, one of the stations showed a decline in both the rainy days and the total amount of rainfall after the mid 1950s[5]. While in Turkey, the trend within a 64 year period (1929-1993 of rainfall for 96 stations were Partal examined).

The overall result indicated that the trend in precipitation is downward, nonetheless, there are few stations that showed increasing trend[6].

Water is indeed life and thus, it's the most important natural resource without which life would be non-existent. Availability of safe and reliable source of water is an essential prerequisite for sustained development[7]. In Tamilnadu India, SARIMA (0,1,1) x $(0,1,1)_{12}$ was found the best fitted model for monthly rainfall[8,9]. For Malaaca and Kuantan in Malaysia, SARIMA models of order (1, 1, 2)x$(1, 1, 1)_{12}$ and (4, 0, 2)x$(1, 0, 1)_{12}$ respectively were fitted for monthly rainfall[10].

A periodical rainfall data was modelled for Port Harcourt city, South-Southern Nigeria using SARIMA (0, 0, 0) x $(2, 1, 0)_4$ model[11]. Modelling seasonal rainfall data was also investigated in Port Harcourt and SARIMA (5,1,0)$(0,1,1)_{12}$ was identified and established to be adequate for modelling and forecasting the amount of rainfall in the area[12]. Rainfall data pattern was examined in Ashanti region of Ghana and SARIMA (0,0,0)x$(2, 1,0)_{12}$ was fitted[13].

SARIMA model was adopted in studying monthly rainfall data for Gadaref rainfall station, Sudan. The autocorrelation structure suggests three multiplicative SARIMA models, namely: (0, 0, 0) x $(0, 1, 1)_{12}$, (0, 0, 1)x$(0, 1, 1)_{12}$ and (0, 0, 1)x$(2, 1, 1)_{12}$. The first model was deemed most appropriate for forecasting rainfall in the region[14]. The seasonal ARIMA modelling and forecasting of rainfall in Warri Town, Nigeria for the period 2003-2012 was examined and the Seasonal ARIMA (1, 1, 1) $(0, 1, 1)_{12}$ was found to meet the criterion of model parsimony and model adequacy checks showed that the model was appropriate[15]. Again, using monthly data spanning from 1996 to 2011 obtained from National Root Crops Research Institute Umudike in Nigeria, SARIMA (0, 0, 0) $(0, 1, 1)_{12}$ model was considered the best fitted model for forecasting monthly rainfall in Umuahia, Aba state[16].

Time series analysis of monthly rainfall for Oshogbo Osun State, Nigeria was studied using data from 2004-2015. The time plot reveals that rainfall data showed high level of volatility characterized by seasonal and irregular variations. The logistic model applied was preferred and then used to forecast rainfall for the next 2 years[17].

Port Harcourt yearly rainfall pattern was studied and ARMA (1, 2) model was found to be most appropriate[18]. Monthly Rainfall forecast over the Sahel region (Katsina Zamfara, Maiduguri, Sokoto, Yobe states) using SARIMA Models were studied and the results indicated no difference between forecast generated from the model[19]. In Imo state, Nigeria, nine (9) different SARIMA models were identified for monthly rainfall and compared based on AIC, SARIMA (0,0,0) x $(1,1,1)_{12}$ was preferred for predicting monthly rainfall in the state[20].

SARIMA models were also compared with ASARIMA models where the univariate time series data is regularly stationary and purely showed seasonal non-stationary characteristics. Using Enugu monthly rainfall (EMR) AIC showed that ASARIMA $+(2,1,1)_{12}$ was preferred to all sub-classes of SARIMA models that were identified[22].

The applications of time series modelling and forecasting have become a major tool in water resources engineering and environmental management fields. The effects of climate change and demand for water in the 21st century made time series analysis of rainfall more imperative than ever before. The major challenges of water demand management is the ability to effectively estimate the contribution of rainfall to the water budget of any given basin.

**Method and Sources of Data Collection:** The rainfall data is obtained from published statistical bulletin by central bank of Nigeria (CBN) 2019[20] and in collaboration with Metrological office Warri. And the rainfall data covered the period of 1981M1-2016MM12 consisting of 432 observations.

**Variable Measurement:** The instrument for measuring rainfall is known as rain gauge. It is a special kind of drum used to record the depth of rainfall collected and it is measured in millimetre.

**Framework of SARIMA model:** Situation where univariate time series $\{X_t\}$ exhibits non-stationary characteristics as a result of either outliers, random walk, drift, trend, or changing variance, it is conservative to take first or second difference (d) to achieve stationarity. Hence, $\{X_t\}$ follows an autoregressive integrated moving average ARIMA (p, d, q) model of orders p, d and q of the form

$$A(L)\nabla^d X_t = B(L)u_t \tag{1}$$

where $\{X_t\}$ exhibits seasonal pattern that is non-stationary, which may likely be observable via correlogram. Box and Jenkins[1] suggested that *SARIMA (p, d, q)×(P, D, Q)*$_S$ is given as

$$A(L)\Phi\left(L^S\right)\nabla^d \nabla_S^D X_t = B(L)\Theta\left(L^S\right)u_t \tag{2}$$

where $\Phi\left(L^s\right)$ denotes lagged seasonal AR operator of order P and $\Theta\left(L^s\right)$ denotes lagged seasonal MA operators of order Q. The operator $\nabla^d = 1 - L$ is the regular differencing operator with $d \leq 2$. The $\nabla_s^D = 1 - L^s$ is seasonal differencing operator and *s* is the seasonal order.

**Adjusted SARIMA Model:** According to Amaefula[18], conditions where univariate time series data is regularly stationary and purely exhibits a seasonal non-stationary characteristics, ASARIMA $(P, D, Q)_{12}$ can be fitted on the assumption that $A(L) = 1$, $\mathrm{B(L)} = 1$, *d=0* and *D=1* so that (2) can be re-written as;

$$\Phi(L_S)\nabla_S X_t = \Theta(L_S)u_t \quad (3)$$

Note that $\Phi(L_s)$ represents the seasonal autoregressive (SAR) operator and it is given as $\Phi(L_s) = 1 - \phi_1 L_{s\times 1} - \cdots - \phi_P L_{s\times P}$ and $\Theta(L_s)$ represents the seasonal moving average (SMA) operator, and it's given as $\Theta(L_s) = 1 - \theta_1 L_{s\times 1} - \cdots - \theta_Q L_{s\times Q}$ .

Generally, the Adjusted SARIMA $(P,D,Q)_s$ model is hereafter known as ASARIMA$(P,D,Q)_s$ model with the inbuilt constant term is of the form;

$$\nabla_S X_t = \omega + \phi_1 \nabla_S X_{t-(s\times 1)} + \cdots + \phi_P \nabla_S X_{t-(s\times P)} + \theta_1 u_{t-(s\times 1)} + \cdots + \theta_Q u_{t-(s\times Q)} \quad (4)$$

where $\omega$ is the constant parameter and $s$ is the seasonality index. And ASARIMA $(P,D,Q)_s$ model is a special case of SARIMA (p,d,q) $(P,D,Q)_s$ model where the non-seasonal parameters are redundant.

**Model Identification:** The autocorrelation function (ACF) and partial autocorrelation function (PACF) will be used in identifying SARIMA model. For MA(q) model, the ACF cuts off after lag q while for an AR(p) model, the ACF is a mixture of sinusoidal tailing off slowly. But the PACF of an MA(q) model tails off slowly whereas that of AR(p) model cuts off after lag p. The AR and MA models are known to show some duality relationships. In model building, it is prudence to prefer the use of mixed ARMA fit to either the pure AR or the pure MA fit.

**Unit Root test:** The unit root test is based on Augmented Dickey Fuller (ADF) test and is of the form

$$\nabla y_t = \alpha + \alpha_1 t + \beta y_{t-1} + \sum_{i=1}^{k} \xi_i \nabla y_{t-i} + a_t \quad (5)$$

where k is the number of lagged variables. In (7) there is the intercept term, drift term and deterministic trend. ADF unit root tests the null hypothesis $H_0 : \beta = 0$ and alternative $H_a : \beta < 0$. According to Dickey and Fuller[2], if the ADF test statistic is greater than 1%, 5% and 10% critical values, the null hypothesis of a unit root test is accepted.

**Model Comparison using SSDFC:** Different model selection criteria have been used to select the best performing model in literature such as; Aikaike information criterion (AIC) and Bayesian information criterion (BIC), residual sum of squares and so on. In this study, SSDFC will be used as model selection criterion. The AIC and BIC can be computed using the formula presented in (4);

$$\left.\begin{array}{l} AIC = 2\times k + n\times \ln(RSS/n) \\ \mathrm{BIC} = 2\times \mathrm{k} + \ln(\mathrm{RSS/n}) + \mathrm{k}\times(\ln \mathrm{n/n}) \end{array}\right\} \quad (6)$$

In (4), $n$ denotes the sample size, $k$ represents the number of parameters estimated in the model, and RSS represents residual sum of squares. BIC penalizes free parameters more than AIC. But for this study, sum of squares deviation forecast criterion introduced by Amaefula [9] will be used for model selection. And it is of the form;

$$SSDFC = \frac{1}{m}\sum_{j=1}^{m}(y_{t(l,j)} - \hat{y}_{t(l,j)})^2 \quad (7)$$

where $l$ is the lead time, $m$ is the number of forecast values and should be reasonably large, $y_{t(l,j)}$ denote actual values of the variable corresponding to the $j^{th}$ position of the forecast values and $\hat{y}_{t,(l,j)}$ is the generated forecasts corresponding to the $j^{th}$ position of the actual values. Using output based criterion to fit models, the model with the least value of SSDFC is the preferred fitted model. SSDFC is describes how well the fitted model can generate forecast values that are much related to the actual values with the highest precision.

**Estimation Method:** The identified SARIMA and ASARIMA models were estimated via iterative algorithm that calculates least squares estimates. The back forecasts at each iteration is computed and sum of squares error is calculated. See Box and Jenkins 1979[2] for more details.

## Results and discussion

This section presents the graphical representation of Warri monthly rainfall (WMRF) data, estimates of ADF unit root test analysis, correlograms, model comparison using SSDFC and estimates of the fitted *ASARIMA* $(P, D, Q)_s$ model.

The time series plot in Figure-1 indicates that WMRF exhibits seasonal oscillation, and July – September accounting for the highest rainfall seasonally.

The result in Table-1 above shows that the order of integration of WMRF data is zero I(0), meaning that the variable is stationary at 1% level of significance.

**Correlogram of WMRF data:** The autocorrelation (AC) and partial autocorrelation (PAC) plots are known as correlogram (ACF and (PACF) and they are used for model identification as presented in Figure-2, 3.

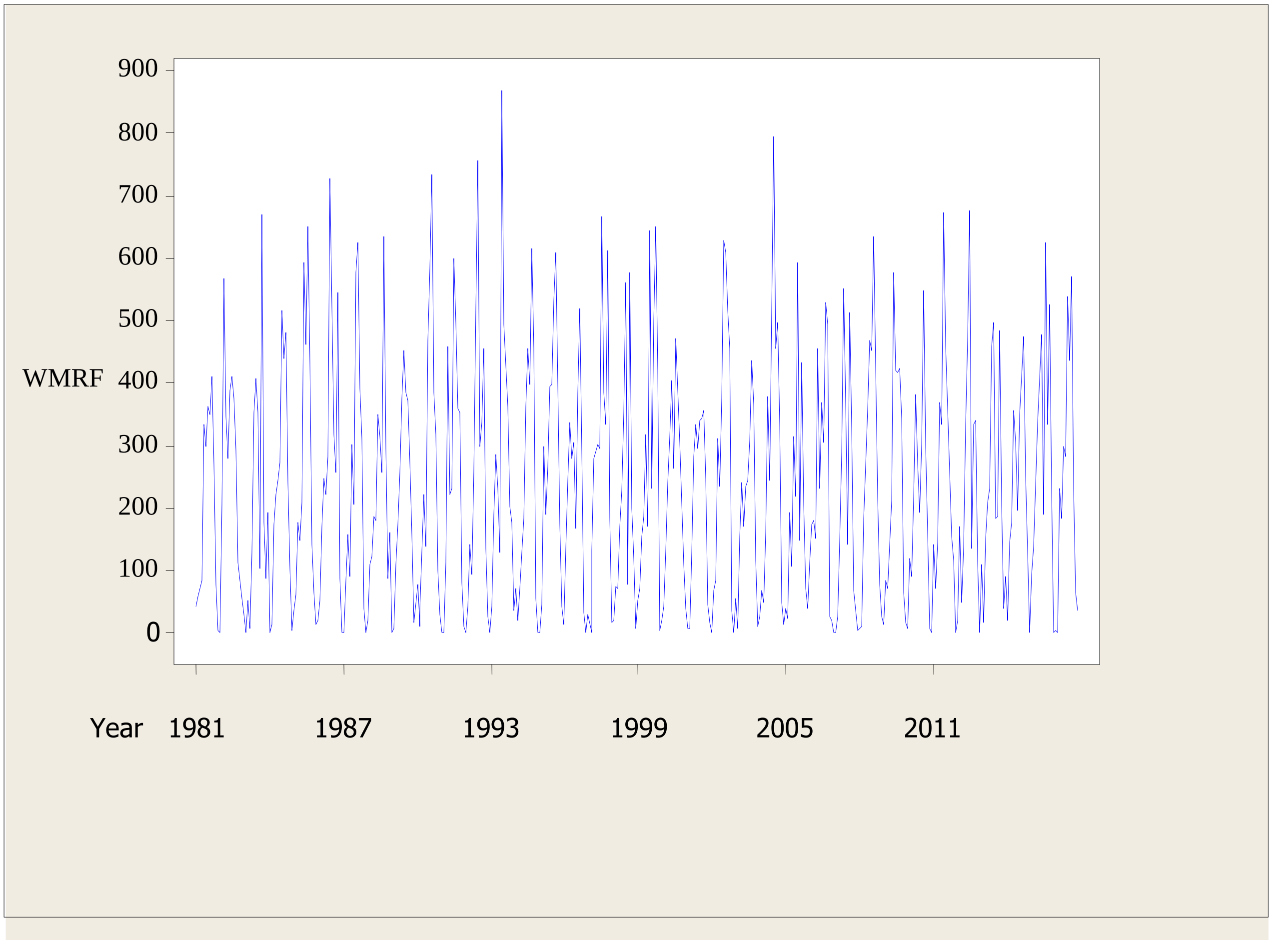


**Figure-1:** Time plot of WMRF from 1981M1 – 2016M12.

**Table-1:** Analysis of Unit Root Test using ADF.

| Null Hypothesis: WMRF has a unit root | | | |
|---|---|---|---|
| Exogenous: Constant | | | |
| Lag Length: 11 (Automatic - based on SIC, maxlag=15) | | | |
| Augmented Dickey-Fuller test statistic | | t-Statistic | Prob.* |
| | | -5.627759 | 0.0000 |
| Test critical values: | 1% level | -3.451993 | |
| | 5% level | -2.870964 | |
| | 10% level | -2.571862 | |

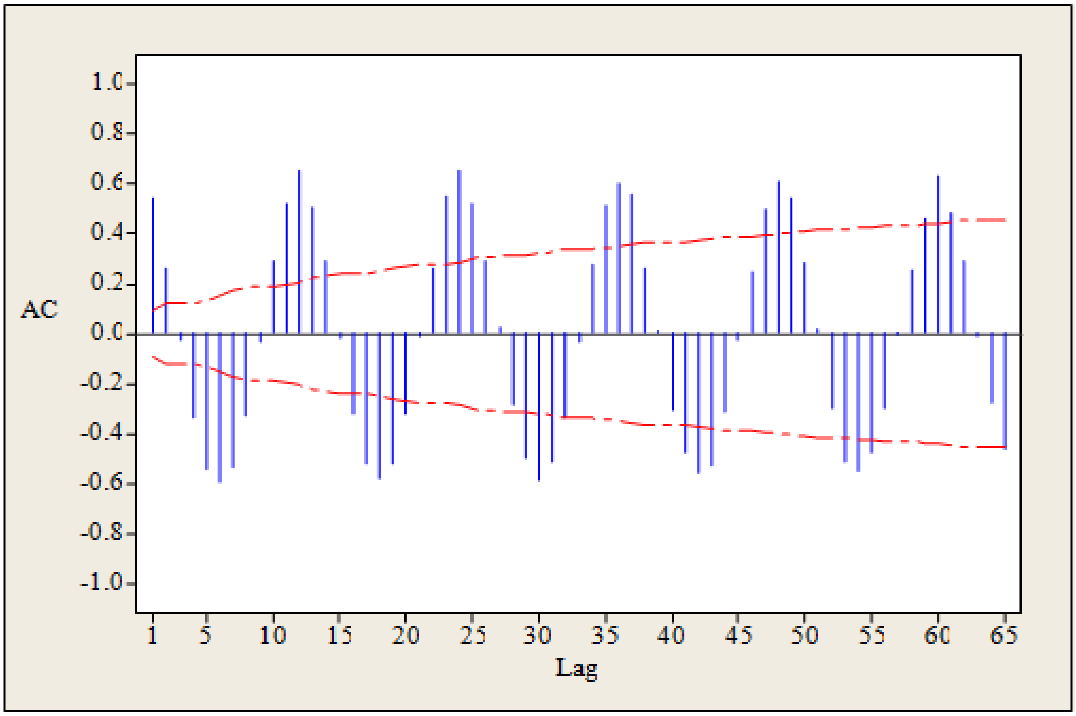


**Figure-2:** Autocorrelation function (ACF) of WMRF.

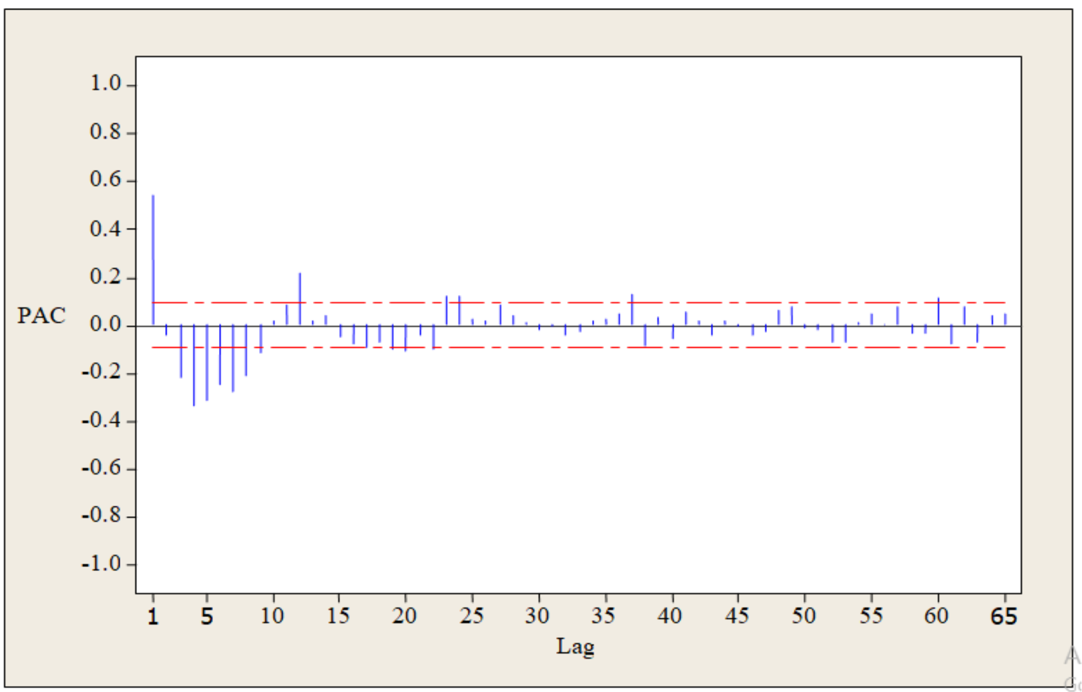


**Figure-3:** PACF of WMRF data.

It is observable that ACF in Figure-2 reveals the presence of seasonal effect in WMRF data hence, seasonal difference (where D=1) is necessary to make the data seasonally stationary.

It is observable that the ACF and PACF in Figure-2, 3 showed that WMRF data exhibited seasonal nonstationary behaviour. The PACF showed seasonal spikes at the 12$^{th}$ and 24$^{th}$ lags. The gradual dwindling of the spikes in Figure-2 signifies seasonal nonstationary behaviour of WMRF data. The PACF periodicity is very visible at every 12$^{th}$ lag spike in Figure-3 suggesting the need for seasonal difference at 12$^{th}$ lag.

**Table-2:** SARIMA and ASARIMA comparison using SSDFC (output based criterion).

| Identified Models | AIC | BIC | RSS | SSDFC |
|---|---|---|---|---|
| $SARIMA(1,0,0)\times(1,1,1)_{12}$ | 4053.24 | 17.4202 | 5037471 | 11793.2 |
| $SARIMA(2,0,0)\times(1,1,1)_{12}$ | 4052.30 | 19.4274 | 5003224 | 11829.4 |
| $SARIMA(3,0,0)\times(1,1,1)_{12}$ | 4053.52 | 21.4397 | 4994244 | 11812.3 |
| $SARIMA(4,0,0)\times(1,1,1)_{12}$ | 4054.75 | 23.4519 | 4985313 | 11808.6 |
| $SARIMA(5,0,0)\times(1,1,1)_{12}$ | 4055.24 | 25.4625 | 4967938 | 11686.8 |
| $SARIMA(0,0,1)\times(1,1,1)_{12}$ | 4053.23 | 17.4201 | 5037305 | 11792.6 |
| $SARIMA(0,0,2)\times(1,1,1)_{12}$ | 4051.97* | 19.4267 | 4999456 | 11826.5 |
| $SARIMA(0,0,3)\times(1,1,1)_{12}$ | 4052.87 | 21.4382 | 4986736 | 11808.2 |
| $SARIMA(0,0,4)\times(1,1,1)_{12}$ | 4054.11 | 23.4504 | 4977984 | 11802.4 |
| $SARIMA(1,0,0)\times(1,1,0)_{12}$ | 4199.66 | 15.7497 | 7102626 | 13488.5 |
| $SARIMA(0,0,1)\times(1,1,0)_{12}$ | 4199.55 | 15.7494 | 7100716 | 13487.7 |
| $SARIMA(0,0,1)\times(0,1,1)_{12}$ | 4052.20 | 15.4083 | 5048607 | 11815.2 |
| $SARIMA(1,0,0)\times(0,1,1)_{12}$ | 4052.16 | 15.4082 | 5048141 | 11811.1 |
| $SARIMA(1,0,0)\times(1,1,2)_{12}$ | 4055.20 | 19.4341 | 5036968 | 11724.5 |
| $SARIMA(1,0,0)\times(1,1,3)_{12}$ | 4056.60 | 21.4468 | 5030012 | 11769.3 |
| $SARIMA(1,0,0)\times(1,1,4)_{12}$ | 4046.69 | 23.4333 | 4893248 | 11698.5 |
| $SARIMA(1,0,0)\times(1,1,5)_{12}$ | 4044.25 | 25.4370 | 4843196 | 11868.1 |
| $ASARIMA(1,1,0)_{12}$ | 4198.34 | 13.7372 | 7113857 | 13509.8 |
| $ASARIMA(2,1,0)_{12}$ | 4172.59 | 15.6870 | 6671164 | 13312.0 |
| $ASARIMA(3,1,0)_{12}$ | 4143.54 | 17.6292 | 6208550 | 13354.0 |
| $ASARIMA(4,1,0)_{12}$ | 4091.26 | 19.5176 | 5475457 | 13127.7 |
| $ASARIMA(1,1,1)_{12}$ | 4051.29 | 15.4062 | 5038060 | 11793.9 |
| $ASARIMA(2,1,1)_{12}$ | 4052.97 | 17.4195 | 5034273 | 11743.4 |
| $ASARIMA(3,1,1)_{12}$ | 4176.28 | 19.7144 | 6666470 | 13220.5 |
| $ASARIMA(0,1,1)_{12}$ | 4050.21 | 13.3943* | 5048719 | 11814.2 |
| $ASARIMA(0,1,2)_{12}$ | 4051.23 | 15.4061 | 5037292 | 11725.9 |
| $ASARIMA(0,1,3)_{12}$ | 4052.62 | 17.4187 | 5030199 | 11771.7 |

| | | | | |
|---|---|---|---|---|
| $ASARIMA(0,1,4)_{12}$ | 4043.74* | 19.4076 | 4905102 | 11857.6 |
| $ASARIMA(1,1,2)_{12}$ | 4053.28 | 17.4203 | 5037873 | 11731.6 |
| $ASARIMA(1,1,3)_{12}$ | 4053.15 | 19.4294 | 5013096 | 11584.5** |
| $ASARIMA(1,1,4)_{12}$ | 4055.71 | 21.4447 | 5019646 | 11689.3 |

The symbol (**) marked the smallest SSDFC value in Table-2.
In Table-2 above, 31 models (17 SARIMA models and 14 possible ASARIMA models) were compared using SSDFC and the model with the smallest value of SSDFC will be preferred and fitted for generating forecasts. From Table-2, *ASARIMA* $(1,1,3)_{12}$ model is chosen as the best fitted model since it has the smallest value of SSDFC. Moreover, AIC and BIC prefer $ASARIMA(P,D,Q)_{12}$ model framework to $SARIMA(p, d, q) \times (P,D,Q)_{12}$. Hence, the estimates of *ASARIMA* $(1,1,3)_{12}$ parameters are presented below;

Note that in Table-3, regular differencing is zero(0), seasonal differencing is one, sample size is 432 and following seasonal differencing, the sample size reduced to 420. Residuals sum of squares (R SS) = 5013096 (back forecasts excluded), mean of squares (MS) = 12080 and degree of freedom (DF) = 415. The estimated *ASARIMA* $(1,1,3)_{12}$ model can be written as presented in Equation (8) below;

$$\nabla_{12} X_t = 0.1645 - 0.5877 X_{t-12} + 0.3925 u_{t-12} + 0.5075 u_{t-24} + 0.0223 u_{t-36} \quad (8)$$

The p-values of Chi-Square statistic in Table-4, are not significant, indicating that the residuals of the fitted model are not auto correlated up to $48^{th}$ lag. Therefore, the fitted *ASARIMA* $(1, 1, 3)_{12}$ model is adequate.

Since there are no significant spikes in the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the model residuals as shown in Figure-4, 5 then, the residuals are uncorrelated and the fitted ASARIMA model for WMRF is adequate and can be used to make forecasts.

The diagnostic test using histogram of residuals in Figure-6 above indicates that the model residuals are normally distributed. Hence, the model fitted is adequate.

**Table-3:** Final estimates of parameters.

| Type | Coef. | SE Coef. | T | P |
|---|---|---|---|---|
| SAR 12 | -0.5877 | 0.7067 | -0.83 | 0.406 |
| SMA 12 | 0.3925 | 0.7073 | 0.55 | 0.579 |
| SMA 24 | 0.5075 | 0.7125 | 0.71 | 0.477 |
| SMA 36 | 0.0223 | 0.0681 | 0.33 | 0.743 |
| Constant | 0.1645 | 0.6150 | 0.27 | 0.789 |

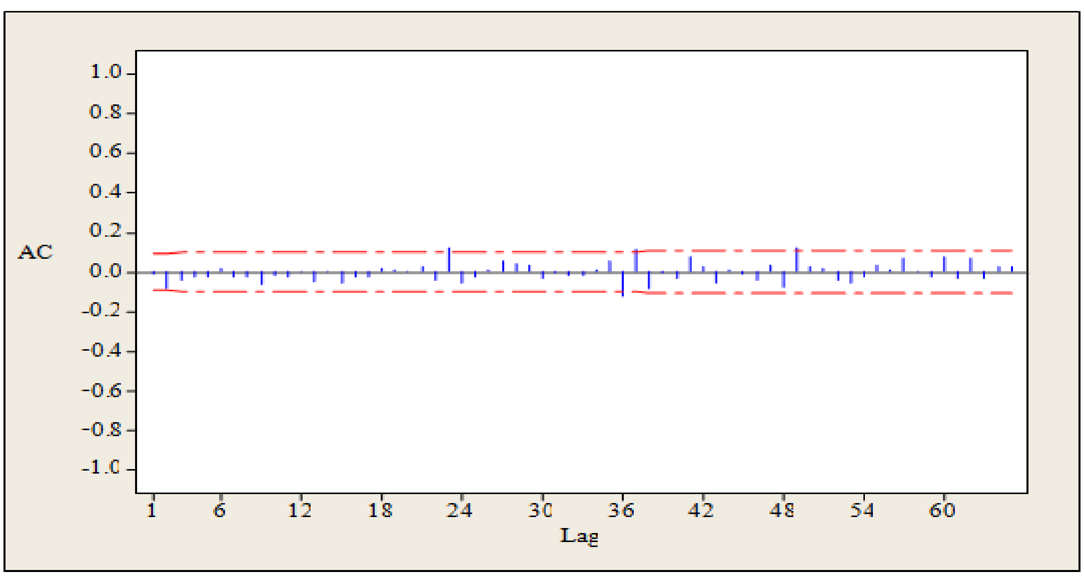

**Figure-4:** Plot of ACF residuals for Warri monthly Rainfall (WMRF).

**Table-4:** Autocorrelation test using Modified Box-Pierce Test.

| Lag | 12 | 24 | 36 | 48 |
|---|---|---|---|---|
| Chi-Square | 6.9 | 19.7 | 32.0 | 51.5 |
| DF | 7 | 19 | 31 | 43 |
| P-Value | 0.434 | 0.411 | 0.415 | 0.176 |

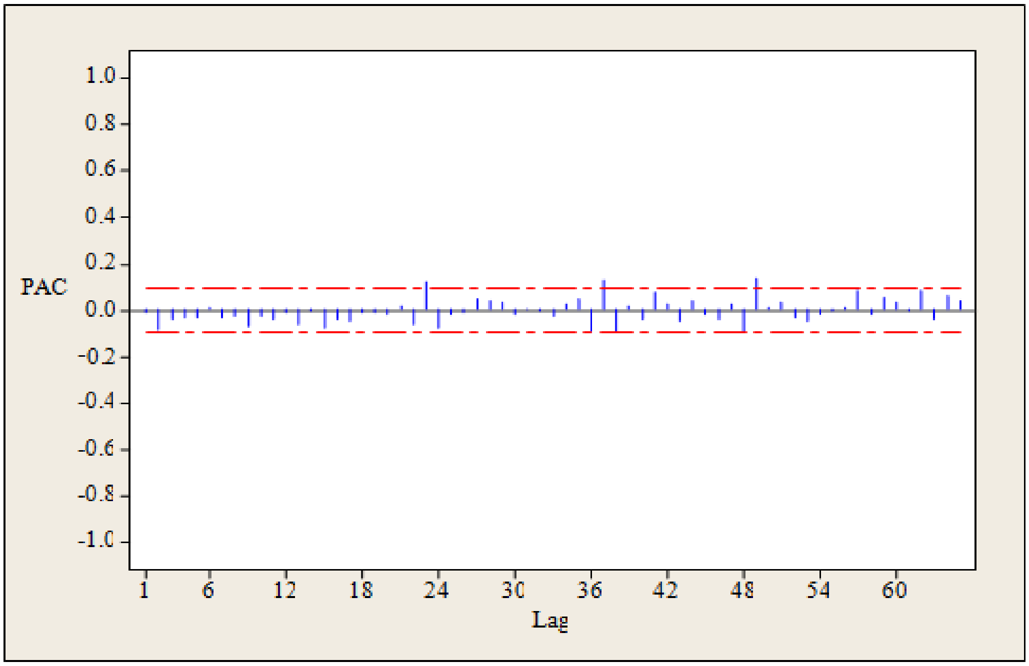


**Figure-5:** Plot of PACF residuals for Warri monthly Rainfall (WMRF).

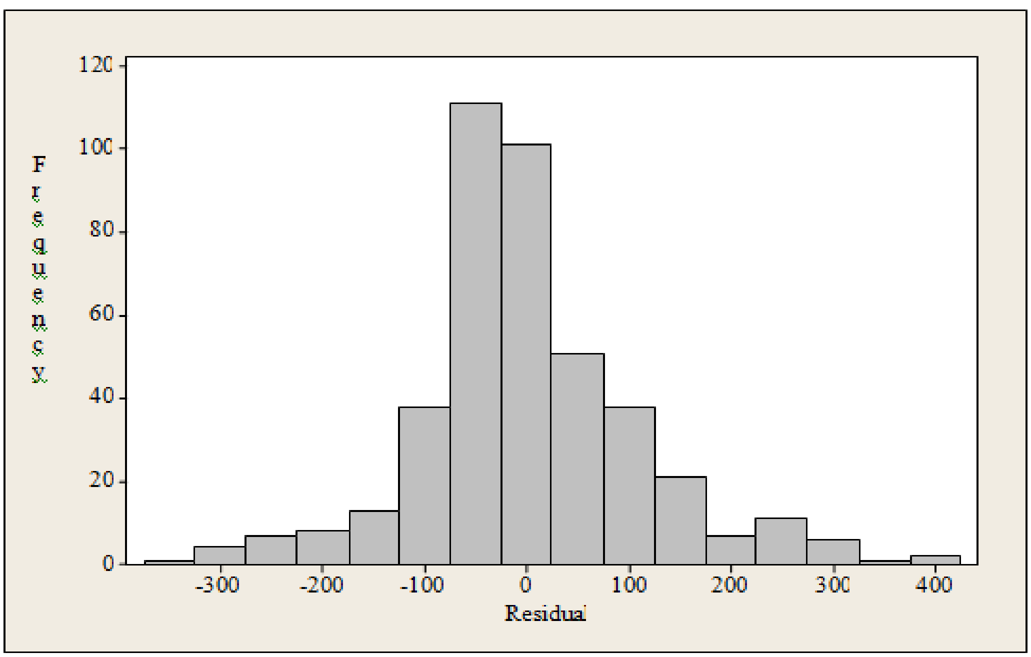


**Figure-6:** Histogram of Residual for the fitted WMRF model.

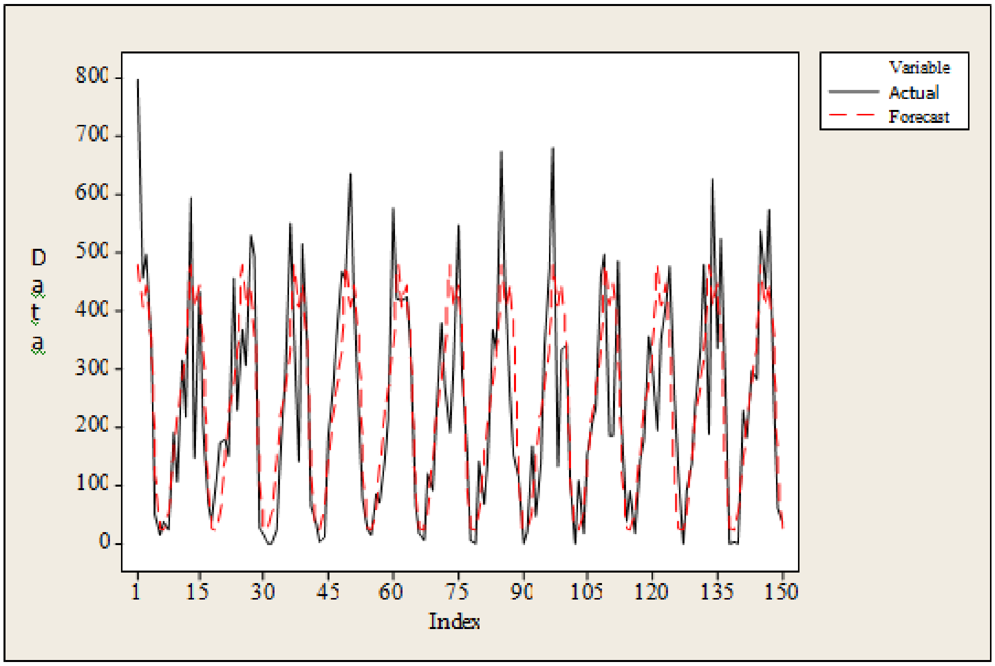


**Figure-7:** Plot of actual and forecast values using the fitted WMRF model (lead time = 150, origin =300).

The forecast values generated using the fitted *ASARIMA* $(1,1,3)_{12}$ model are very close to their actual values.

**Discussion of Results:** The WMRF data is found to be stationary, significant at 1% level. The ACF in Figure-2 reveals that WMRF has seasonal characteristics and the PACF showed seasonal spikes at the $12^{th}$ and $24^{th}$ lags indicating that the data requires seasonal differencing in the model.

Comparing 17 possible seasonal ARIMA models with 14 possible ASARIMA models using SSDFC showed that *ASARIMA*$(1,1,3)_{12}$ is most appropriate. This finding differs from that of Eni and Adeyeye[12] that fitted *SARIMA*$(1,1,1)\times(0,1,1)_{12}$ model for forecasting rainfall in Warri Town, Nigeria for the period 2003-2012.

The results of our model diagnostic test showed that the fitted model is adequate. And the generated forecast values are quite similar with the actual values.

## Conclusion

The finding of the project reveals that out of 31 models; 17 possible seasonal ARIMA models and 14 possible ASARIMA models fitted, *ASARIMA* $(1,1,3)_{12}$ model was found most appropriate using SSDFC (an output based model selection criterion). Nevertheless, even AIC and BIC preferred ASARIMA model framework model to SARIMA model.

However, in a regularly stationary series but seasonally nonstationary, ASARIMA model framework is preferable to reduce parameter redundancy. Therefore, *ASARIMA* $(1,1,3)_{12}$ model is recommended for forecasting WMRF pattern, flood prediction and control in Warri, Delta state.

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